Supplementary Data

Table S1. *Tabulated TRIPOD Checklist*

Section/Topic	Item	Checklist Item	Page/Comments
Title and Abstract	1	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.	Title: This study looks at a prediction model using radiomic features of PET/CT to predict AAA growth rate.
Title and Abstract	2	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions.	Abstract: The abstract covers a summary of all the requested information.
Introduction	3a	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models.	a) The introduction presents the background of AAAs and the aim of creating an ML model using radiomic features derived from FDG PET-CT. No existing models using these features exist for comparison.
Introduction	3b	Specify the objectives, including whether the study describes the development or validation of the model or both.	b) The aim is to develop an ML-based model using radiomic features derived from FDG PET-CT.
Methods	4a	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data sets, if applicable.	a) This is a retrospective cohort study. Data was split into training and testing datasets. K-fold cross-validation was used.
Methods	4b	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up.	b) Patients with AAA who underwent FDG PET-CT from January 2009 to March 2020 were included.
Methods	5a	Specify key elements of the study setting, including number and location of centres.	a) Single tertiary centre study.
Methods	5b	Describe eligibility criteria for participants.	b) Excluded patients who had undergone AAA surgery or EVAR.
Methods	5c	Give details of treatments received, if relevant.	c) PET-CT scans were acquired as part of oncology workups, not for AAA treatment.
Methods	6a	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.	a) Outcomes are defined based on clinical records.
Methods	6b	Report any actions to blind assessment of the outcome to be predicted.	b) Investigator was blinded to imaging parameters when reviewing clinical records.
Methods	7a	Clearly define all predictors used in developing or validating the multivariable prediction model, including how and when they were measured.	a) Radiomic features extracted, with detailed descriptions included in methods.
Methods	7b	Report any actions to blind assessment of predictors for the outcome and other predictors.	b) Images were contoured and analyzed without reference to outcome data.

Methods	8	Explain how the study size was arrived at.	Limited number of patients available due to FDG PET-CT not being standard for AAA.
Methods	9	Describe how missing data were handled.	Only complete datasets were used.
Methods	10a	Describe how predictors were handled in the analyses.	Predictors included radiomic features and serial ultrasound measurements.
Methods	10b	Specify type of model, all model-building procedures, and method for internal validation.	Recursive feature elimination with random forest regression; multilayer perceptron CNN model.
Methods	10d	Specify all measures used to assess model performance and compare models.	Mean absolute error (MAE) metric used for performance evaluation.
Methods	11	Provide details on how risk groups were created, if done.	Risk groups were not created.
Results	13a	Describe the flow of participants through the study.	Consecutive patients identified retrospectively. Flow described in methods.
Results	13b	Describe characteristics of the participants.	Patient demographics presented in Table 3.
Results	14a	Specify the number of participants and outcome events in each analysis.	Outlined in methods and figures.
Results	14b	Report the unadjusted association between each candidate predictor and outcome.	Not performed.
Results	15a	Present the full prediction model to allow predictions for individuals.	Full architecture described in methods and illustrated in Figure 2.
Results	15b	Explain how to use the prediction model.	Instructions for use outlined in manuscript.
Results	16	Report performance measures for the prediction model.	Results provided with performance measures (MAE) and uncertainty quantification.
Discussion	18	Discuss any limitations of the study.	Limitations include retrospective design, single-centre focus, and lack of external validation.
Discussion	19b	Give an overall interpretation of the results.	Results highlight the model's potential for personalized AAA treatment.
Discussion	20	Discuss clinical use and implications for future research.	Discussion section explores clinical utility and future research potential.
Other Information	21	Provide information about supplementary resources.	Resources referenced in manuscript.
Other Information	22	Give the source of funding and the role of the funders for the present study.	No external funding. No conflicts of interest.

Table S2. *PyRadiomic Customised Settings*

Level	Category	Setting	Setting Value	Explanation
Feature Extractor Level	Image Normalisation	normalise	true	Normalises the image by centering it at the mean with standard deviation. Normalisation is based on all gray values in the image, not just those inside the segmentation.
	Resampling the image	resampledPixelSpacing	[2, 2, 2]	Resampling the voxel spacing to standardise all scans.
Feature Class Level	Image discretization	binWidth	0.5	Size of the bins when making a histogram and for discretization of the image gray level.
Voxel-based specific settings		initValue	nan [2]	Value to use for voxels outside the ROI [1], or voxels where calculation failed. If set to nan [2] will be treated as transparent voxels.

		voxelBatch	10000	This value controls the maximum number of voxels that are calculated in one batch. Larger batches mean less loops in Python and therefore a quicker extraction, but do require more memory.

[1] ROI: Region of Interest, [2] nan: Not a Number

Table S3. *Radiomic Feature Classes*

Feature class	Number of features

First Order Statistics (19 features)	18
Gray Level Co-occurrence Matrix (24 features)	24
Gray Level Run Length Matrix (16 features)	16
Gray Level Size Zone Matrix (16 features)	16
Neighbouring Gray Tone Difference Matrix (5 features)	5
Gray Level Dependence Matrix (14 features)	14
Total	93

Note: Distribution of features across six feature classes. The total number of extracted features is 93, with individual contributions from First Order Statistics (18 features), Gray Level Co-occurrence Matrix (24 features), Gray Level Run Length Matrix (16 features), Gray Level Size Zone Matrix (16 features), Neighbouring Gray Tone Difference Matrix (5 features), and Gray Level Dependence Matrix (14 features).

Table S4. *All Radiomic Features*

Feature Class	Feature Count	Feature Names
First Order	18	10Percentile, 90Percentile, Energy, Entropy, InterquartileRange, Kurtosis, Maximum, Mean, MeanAbsoluteDeviation, Median, Minimum, Range, RobustMeanAbsoluteDeviation, RootMeanSquared, Skewness, TotalEnergy, Uniformity, Variance
Gray Level Co-occurrence Matrix	24	Autocorrelation, ClusterProminence, ClusterShade, ClusterTendency, Contrast, Correlation, DifferenceAverage, DifferenceEntropy, DifferenceVariance, Id, Idm, Idmn, Idn, Imc1, Imc2, InverseVariance, JointAverage, JointEnergy, JointEntropy, MCC, MaximumProbability, SumAverage,

		SumEntropy, SumSquares
Gray Level Run Length Matrix	16	GrayLevelNonUniformity, GrayLevelNonUniformityNormalized, GrayLevelVariance, HighGrayLevelRunEmphasis, LongRunEmphasis, LongRunHighGrayLevelEmphasis, LongRunLowGrayLevelEmphasis, LowGrayLevelRunEmphasis, RunEntropy, RunLengthNonUniformity, RunLengthNonUniformityNormalized, RunPercentage, RunVariance, ShortRunEmphasis, ShortRunHighGrayLevelEmphasis, ShortRunLowGrayLevelEmphasisShortRunLowGrayLevelEmphasis
Gray Level Size Zone Matrix	16	GrayLevelNonUniformity, GrayLevelNonUniformityNormalized, GrayLevelVariance, HighGrayLevelZoneEmphasis, LargeAreaEmphasis, LargeAreaHighGrayLevelEmphasis, LargeAreaLowGrayLevelEmphasis, LowGrayLevelZoneEmphasis, SizeZoneNonUniformity, SizeZoneNonUniformityNormalized, SmallAreaEmphasis, SmallAreaHighGrayLevelEmphasis, SmallAreaLowGrayLevelEmphasis, ZoneEntropy, ZonePercentage, ZoneVariance
Gray Level Dependence Matrix	14	DependenceEntropy, DependenceNonUniformity, DependenceNonUniformityNormalized, DependenceVariance, GrayLevelNonUniformity, GrayLevelVariance, HighGrayLevelEmphasis, LargeDependenceEmphasis, LargeDependenceHighGrayLevelEmphasis, LargeDependenceLowGrayLevelEmphasis, LowGrayLevelEmphasis,

			SmallDependenceEmphasis, SmallDependenceHighGrayLevelEmphasis, SmallDependenceLowGrayLevelEmphasis
Neighbouring Gray Tone Difference Matrix	5		Busyness, Coarseness, Complexity, Contrast, Strength

Table S5. *Summary of Machine Learning Models and Performance*

Model	Key Parameters	Feature Selection	Uncertainty Quantification	Internal MAE (Full Features)	Internal MAE (RFE)	External MAE
MLP	Layers: 7; Optimiser: RMSprop; Activation: ReLU; Learning rate: 0.01; Interpolator: NearestNeighbor; Normalize: True; Resampled Pixel Spacing: [2, 2, 2]	RFE	Dropout during inference	$1.35 \pm 3.2e^{-4}$ mm/year	$1.35 \pm 2.5e^{-4}$ mm/year	$1.8 \pm 8.9e^{-8}$ mm/year
Random Forest	Trees: 500; Max depth: 20; Split criterion: Gini index;	RFE	Dropout during inference	$1.5 \pm 3.8e^{-4}$ mm/yea	$1.48 \pm 3.7e^{-4}$ mm/year	$1.95 \pm 6.9e^{-4}$ mm/year

	Kernel Radius: 2					
XGBoost	Trees: 100; Learning rate: 0.1; Max depth: 6; BinWidth: 25; Interpolator: BSpline	RFE	95% Prediction Interval (PI)	$1.42 \pm 4.2e^{-4}$ mm/year	$1.40 \pm 4.0e^{-4}$ mm/year	$1.97 \pm 7.1e^{-4}$ mm/year
SVM	Kernel: RBF; Regularisation (C): 1.0; Gamma: Scale	RFE	N/A	$1.45 \pm 4.1e^{-4}$ mm/year	$1.40 \pm 3.9e^{-4}$ mm/year	$1.90 \pm 7.2e^{-4}$ mm/year

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